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CONSTRUCTION CHANGE ORDER D~~ATA AS INPUTS FOR A PROGRAMMATIC RISK MODEL~~IMPACTS ON LARGE MILITARY CONSTRUCTION PROGRAM

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ABSTRACT: Hurricane Michael struck Tyndall Air Force Base as a Category 5 storm with 160 mph winds, damaging or destroying 90% of its infrastructure (484 buildings). In response, the Department of Defense launched a massive reconstruction effort, rebuilding Tyndall as the "Installation of the Future" through 44 Military Construction (MILCON) projects and 260 Facility Restoration, Sustainment, and Modernization (FRSM) projects. Since reconstruction began, over 630 Change Request Forms (CRFs) have been closed, as of August 2024, adding $67.8 million in costs and 4,880 construction days. The Air Force Civil Engineer Center's (AFCEC) Natural Disaster Recovery (NDR) Division developed a programmatic risk model to predict costs and delays but lacked data-driven rigor. This research analyzed historical CRF data using text mining, categorizing CRFs into six bins—Wastewater, Stormwater, Fire, Electrical, Concrete, and Other—based on keyword analysis. Also, overlapping categories formed composite bins such as Fire and Electrical, Two, or Three+. Statistical analysis revealed significant cost variations. Categories like Fire, Electrical, and Other had the lowest costs, while composite bins such as Fire and Electrical, Two, or Three+ were significantly more expensive. These findings show that using a broad average for cost predictions is inefficient. Instead, categorizing CRFs and applying confidence intervals improves the programmatic risk model's accuracy, enhancing future cost and time impact estimations.

1. INTRODUCTION

Change orders, which modify the scope, cost, or schedule of construction projects, are a primary driver of cost and schedule overruns (Hanna et al., 1999; Syal & Bora, 2016). These changes may arise due to unforeseen site conditions, evolving project requirements, regulatory compliance issues, design modifications, or contractual adjustments (El-adaway et al., 2016; Hwang et al., 2009). While they serve a necessary role in accommodating project evolution, change orders can also introduce financial and operational risks, necessitating effective management strategies.

Despite widespread recognition of the challenges associated with change orders, existing research primarily focuses on transportation infrastructure, particularly highway projects managed by state Departments of Transportation (DOTs) (Nassar et al.,2005; Shrestha et al., 2021). These studies highlight patterns in cost escalations and schedule delays but often lack a comprehensive categorization framework that can be applied across diverse construction projects. This study seeks to fill that gap by analyzing a broader dataset, encompassing various construction sectors beyond transportation, to develop a programmatic risk model that enhances change order management.

The unpredictability of change orders presents a major challenge for construction managers, financial planners, and policy makers. Traditional cost estimation models often rely on aggregate metrics such as mean cost growth, which fail to account for variability among different categories of change orders (Nassar et al.,2005; Shrestha et al., 2021). This research aims to address this shortcoming by categorizing change orders and applying statistical analyses to uncover meaningful patterns in cost impacts. Through this approach, project stakeholders can gain a clearer understanding of which types of changes are most likely to drive budgetary overruns and how to mitigate their effects.

Furthermore, the lack of standardized risk assessment methods for evaluating change orders hinders the ability to develop proactive mitigation strategies (Naji et al.,2022). By leveraging statistical tools such as non-parametric tests, confidence intervals, and categorical classification, this study provides a systematic approach to predicting the financial implications of change orders. The insights derived from this research are expected to improve decision-making in project planning, budgeting, and risk management, ultimately leading to more efficient and cost-effective construction practices.

A critical aspect of this study is the integration of a categorization framework that identifies key cost drivers within different types of change orders. By examining detailed project data from Tyndall AFB, this research demonstrates how text-based analysis of change descriptions and justifications can inform financial forecasting. Additionally, statistical comparisons between categories of change orders provide insights into which modifications have the highest financial impact and require greater scrutiny during project planning.

In summary, this research seeks to contribute to the growing body of knowledge on construction project risk management by offering a structured, data-driven approach to understanding and predicting the financial implications of change orders. Through rigorous statistical analysis and meaningful categorization, this study provides practical recommendations for improving change order management, enhancing cost estimation methodologies, and minimizing financial risks in construction projects.

2. METHODS AND RESULTS

This study utilizes data from the Lifecycle Management Process – Integrated Data Environment (LCMP-IDE), specifically completed CRFs related to construction projects at Tyndall AFB. The dataset was preprocessed to remove inconsistencies and missing values before undergoing text mining and statistical analysis. The research methodology employed to analyze impacts of construction change orders on project costs and timelines is found in Figure 1.

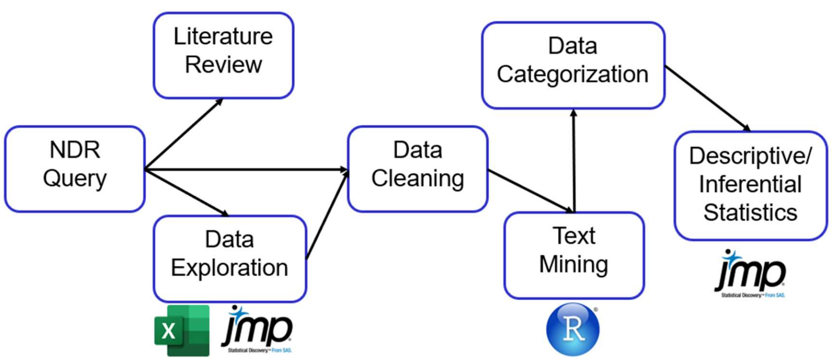

Figure 1: Method Overview

2.1 Data Collection and Processing

The dataset used in this study consists of Change Request Forms (CRFs) collected from a centralized project management database for Tyndall AFB construction projects. These CRFs document various modifications to ongoing projects, including descriptions, justifications, and negotiated modification amounts. The data collection process ensured that all entries were sourced from a singular, authoritative database, with corrections made by project managers as needed to maintain accuracy and completeness.

Each CRF was carefully reviewed to confirm completeness, and any discrepancies were flagged for verification with the relevant project managers. The dataset underwent a structured preprocessing stage, which included standardizing terminology, normalizing financial data to a common unit, and ensuring date consistency. Duplicate entries were identified and removed to prevent data redundancy, while inconsistencies in reported modification amounts were resolved through cross-validation with official project financial records. Only duplicated data was removed from the initial query after verifying the ground truth with the project managers to prevent one valid change from counting as multiple changes. Additionally, all missing fields in the data were updated to actual values by the responsible project manager for each individual project after the authors pointed out the omissions.

2.3 Text Mining and Categorization

Text mining methodologies were applied to analyze the descriptions and justifications provided in the CRFs. First, tokenization was performed to break down textual data into individual words and phrases, ensuring that meaningful terms were extracted. Stop words such as “the,” “and,” and “for” were removed to enhance focus on substantive content. Next, the word frequency analysis identified recurring terms such as “fire,” “concrete,” and “stormwater,” enabling effective categorization of CRFs. Word clouds and bar graphs demonstrated the prevalence of key phrases, reinforcing the classification framework used in the statistical analysis. An example of the most frequent bigrams from the change description column can be found in Figure 2.

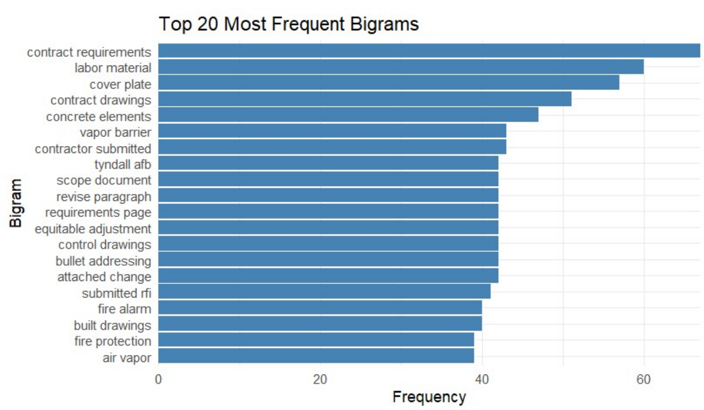

Figure 2~~3~~: Most Frequent Bigrams in Change Descriptions

Further, bigram and trigram analyses were performed to detect common phrase patterns that could indicate specific types of change orders. This method helped in refining categorization by identifying word sequences that frequently co-occurred in justifications. In Figure 2, you can start to get a better understanding of the database as a whole with bigrams such as “concrete elements” or “fire alarm” frequently occurring within the change descriptions. The text mining analysis laid the framework for the categorization of the CRF’s into unique bins.

Change orders were categorized based on common keywords, cost implications, and project-specific contextual factors. The primary categories identified include Fire, Concrete, Electrical, Wastewater, Stormwater, and Other. To account for multi-faceted change orders, additional multi-category groups, such as "Fire and Electrical", “Two”, "Three+," were included for modifications affecting multiple systems or disciplines. The category “Two” includes all CRFs that included two different categories and the category “Three+” includes any CRF that included three or more different categories. This was done to evaluate the impact of simple versus complex CRF impacts.

2.4 Descriptive Statistics

The analysis was conducted using JMP Pro 15, focusing on descriptive statistics to understand the distribution and variation of negotiated modification amounts. Box plots, kernel density plots, and summary statistics were employed to detect skewness and distributional properties. The summary statistics, found in Table 1, shows that the negotiated modification of all the CRF’s had a mean of $61,624.39 and a median of $15,204.78. This is known as a right-skew and the tail of the distribution stretches out further to the right (higher values) and demonstrates that there are a few unusually large numbers (outliers) pulling the mean upward, making it larger than the median.

Table 1: Summary Statistics of the Negotiated Modification Amount

Summary Statistics	Negotiated Mod Amount
Mean	$61,624.39
Median	$15,204.78
Std Dev	$254,414.11
Std Err Mean	$10,136.10
Upper 95% Mean	$81,529.08
Lower 95% Mean	$41,719.69
N	630

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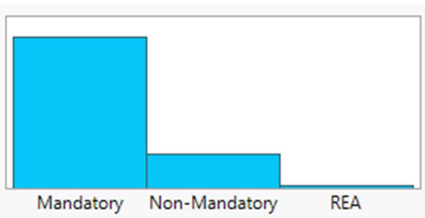
Figure ~~2~~3 shows the frequencies of the type of change the CRF was labeled as and shows the count and probability of the data set on the right hand of the image. Mandatory changes were by far the most frequent at 81.1% followed by non-mandatory changes at 17.8%. This shows that most of the CRF’s had to be accomplished and there was no choice, and the change was not user- driven by the Air Force.



Frequencies

Level	Count	Prob
Mandatory	511	0.81111
Non-Mandatory	112	0.17778
REA	7	0.01111
Total	630	1.00000

N Missing 0
3 Levels

Figure ~~2~~3: Frequencies of the Type of Change the CRF’s

Figure ~~3~~4 shows the frequencies of the CRF’s according to the AF Project Name. Figure ~~3~~4 shows that the Operations/Aircraft Maintenance Hangar 1 had the most CRF’s at 34 followed by the Operations/Aircraft Maintenance Hangar 3 and the Maintenance Squadron Complex both at 32 CRF’s. The Munitions Storage project had the least amount of CRF’s at only ~~1~~one.

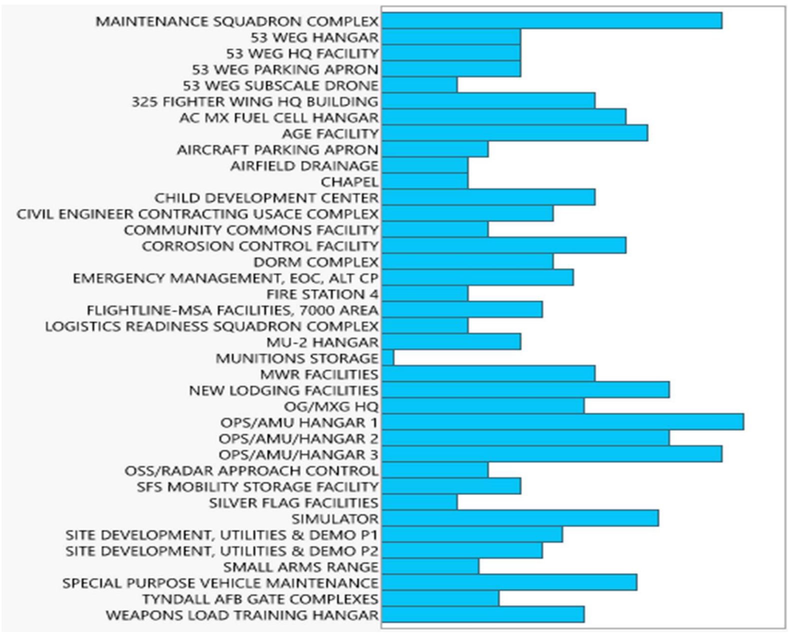
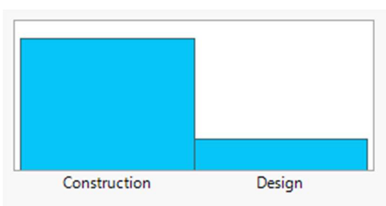


Figure ~~3~~4: Frequency of CRF’s compared to the AF Project Name

Figure ~~4~~5 shows that most of the CRFs historically occurred during the construction phase, where they typically result in higher costs compared to the design phase. Specifically, the mean negotiated modification amount for CRFs during the construction phase was $72,208.95, compared to $16,173.03 for those occurring in the design phase. This significant cost difference highlights the importance of identifying and addressing potential changes earlier in the project lifecycle, where costs can be mitigated more effectively.



Frequencies

Level	Count	Prob
Construction	511	0.81111
Design	119	0.18889
Total	630	1.00000
N Missing	0	
2 Levels		

Figure ~~4~~5: Phase that the CRF Occurred

Figures ~~5~~6 and ~~6~~7 show the box plots and kernel density plots for all the different bins for the CRF’s that contained only one category or bin. The box plots and kernel density plots show that there could potentially be differences between the variances, medians, and means of the groupings but we cannot tell which ones are different from these figures alone, and further statistical analysis is needed.

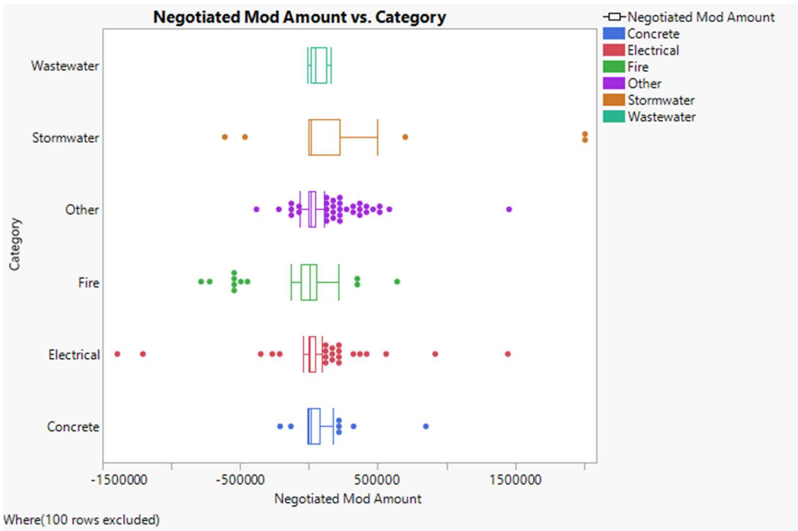


Figure ~~5~~6: Box Plot of Category

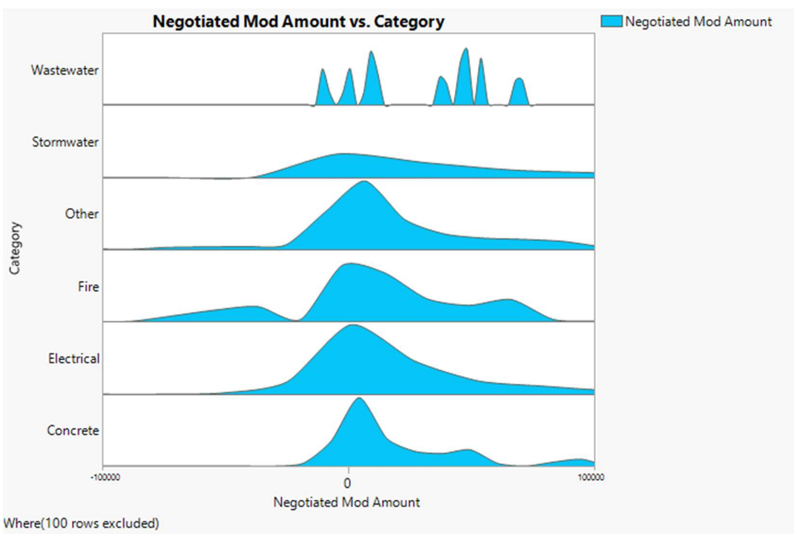


Figure ~~6~~7: Kernel Density Plot of Category

Table 2 shows the summary statistics of the different categories. We can see that all categories, except “Fire”, are right skewed, indicating larger, positive number pulling the mean upwards. The other interesting result from these summary statistics was that the “Fire” category had a negative mean. This big change in the mean with only a little change in the median was caused by a few large changes that descoped or modified the fire protection systems in these projects.

Table 2: Summary Statistics of Category

Category	Mean	Median	UL 95% Mean	LL 95% Mean	N
Concrete	$63,071.58	$13,405.40	$109,545.73	$16,597.42	44
Electrical	$30,900.92	$9,035.33	$72,901.10	-$11,099.26	130
Fire	-$64,952.58	$5,499.50	$30,368.30	-$160,273.50	40
Other	$40,809.18	$9,685.00	$55,617.66	$26,000.69	283
Stormwater	$234,974.37	$17,665.00	$529,421.10	-$59,472.37	21
Wastewater	$62,743.50	$47,834.32	$97,584.08	$27,902.91	13

2.5 Statistical Analysis

Given the non-normal distribution of negotiated modification amounts, non-parametric statistical methods were applied. The Levene and Brown-Forsythe tests were used to compare variances across categories, ensuring that variability in costs was statistically evaluated, and results can be found in Table 4. we reject the null hypothesis that the variances/standard deviations of the bins are statistically equivalent.

Table 3: Metric for comparing variance between categories

Comparing Variance Between Categories				
Test	**F Ratio**	**DFNum**	**DFDen**	**Prob > F**
Brown-Forsythe	10.0378	5	524	<.0001
Levene	18.5016	5	524	<.0001

Welch ANOVA was applied to determine differences in means among the different change order categories, accounting for unequal variances. The Kruskal-Wallis test was employed to assess differences in medians, providing a robust method for evaluating category-level disparities. Additionally, Steel-Dwass pairwise comparisons were conducted to identify significant differences between specific categories. The nonparametric comparison for all CRF pairs that showed a statistical difference is found in Table 4.

Table ~~7~~4: Nonparametric Comparisons For All Pairs Using Steel-Dwass Method

Nonparametric Comparisons For All Pairs Using Steel-Dwass Method					
Level	**- Level**	**p-Value**	**Hodges-Lehmann**	**Lower CL**	**Upper CL**
Wastewater	Other	0.0254	$35,194	$3,508	$58,595
Wastewater	Electrical	0.0339	$33,997	$1,089	$60,346
Wastewater	Fire	0.0368	$52,046	$1,694	$129,483
Stormwater	Fire	0.0329	$58,397	$934	$285,477

These statistical techniques were chosen due to their effectiveness in handling skewed financial data, ensuring that the conclusions drawn from the analysis accurately represent real-world construction change order trends.

3. CONCLUSIONS

This study explores the financial impacts of construction change orders (CRFs) as inputs for a programmatic risk model. By categorizing change orders into distinct bins and employing statistical analysis, it provides valuable insights into cost variations and risk factors across different types of changes.

One of the key findings is the significant cost variability among different categories of change orders. Changes related to "Stormwater" and "Wastewater" exhibited much higher negotiated modification amounts compared to simpler categories such as "Fire" and "Electrical." The mean negotiated modification amount for "Stormwater" was $234,974.37, whereas "Electrical" had a substantially lower mean of $30,900.92. These findings suggest that large-scale infrastructure changes often incur significantly higher costs due to their complexity and extensive resource requirements.

Another major insight is the inefficiency of using the mean as a performance metric. The study found that the overall mean ($61,624.39) was heavily skewed by a few high-value outliers, making it a poor representation of typical costs. Instead, confidence intervals and categorization provide a more accurate understanding of cost distribution and risk exposure. For instance, multi-category CRFs, such as those spanning three or more categories, had an average negotiated modification amount of $355,463.77, emphasizing the compounded risks associated with complex changes

Furthermore, the research highlights the value of categorization in Change Order Management (CHM). Grouping change orders based on their nature allows for more precise risk assessments and resource planning. Categories like "Fire" and "Electrical" involve lower costs, whereas multi-category changes introduce greater financial and logistical challenges.

This study demonstrates that categorizing CRFs significantly enhances cost analysis by providing a clearer understanding of financial risks and enabling more effective project planning. The findings reveal that multi-category CRFs consistently carry higher costs due to the increased complexity and coordination required for their execution. Additionally, the research establishes that relying solely on the mean as a risk metric is ineffective, as it is skewed by extreme values and does not accurately represent the variability in change order costs. Instead, the use of confidence intervals and category-based analysis presents a more reliable method for assessing financial impact. The study also underscores that a detailed categorization approach improves forecasting by capturing the true variability of change orders and their associated risks.

While this research offers meaningful contributions to Change Order Management, it has limitations, including a restricted number of categories and the absence of predictive cost modeling. Future studies could expand categorization frameworks and integrate machine learning models to refine cost estimation and risk assessment methodologies. Ultimately, this research advances Change Order Management by introducing a structured, category-driven approach to evaluating financial impacts, thereby improving risk management and decision-making in construction projects.

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